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San Diego

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ADMINISTRATIVE INFORMATION

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PS

EXECUTIVE SUMMARY

A type of self-optimizing computer algorithm, called evolutionary programming, was used to create a number of models of the dolphin ear. The models consisted of a series of overlapping bandpass filters that varied in sensitivity and bandpass region and were distributed across the range of dolphin hearing. The evolutionary program iteratively varied the shape, number, and distribution of filters in each model and optimized the acoustic sensitivity of the model to the hearing sensitivity of the dolphin. Final models displayed acoustic sensitivities similar to the dolphin across the range of dolphin hearing. These bandpass models are frequency domain filters usable as preprocessors to biomimetic mine countermeasure classification/detection algorithms and auditory weighting functions in environmental compliance issues related to the interaction between marine mammal populations and anthropogenic sound.

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INTRODUCTION

Dolphins demonstrate an unsurpassed ability to detect and identify submerged and buried objects through the use of biological sonar. The dolphin sonar system is tolerant to noise and reverberant environments (Au and Penner, 1981), requires no visual input for target verification/classification (Kellogg, 1958), is capable of detecting buried targets (Helweg et al., 1999; Roitblat et al., 1995), and is robust to targets with aspect-dependent shape (Helweg et al., 1996; Moore and Bivens, 1995). Because of their superb target detection and identification abilities, dolphins have been employed by the Navy Marine Mammal Systems to assist with Mine Countermeasure (MCM) efforts. Dolphin echolocation has also inspired the development of object classifier systems based upon the structural and functional characteristics of dolphin echolocation. Ultimately, these "biomimetic" classifier systems will enhance fleet mine hunting assets.

The "Integrator Gateway Network" (IGN) was developed to test the potential improvement that could be imparted to a spectrum-based neural network classifier through the implementation of echo summation (Moore et al., 1991). Dolphins ensonify targets by directionally emitting a rapid series of damped sinusoids of short duration (Au, 1980; Au et al., 1974) and process the returning echoes. The IGN mimicked this operational characteristic by using the spectrum of a target echo as input. Spectra from subsequent echoes were sequentially submitted to the network to form a cumulative representation of spectral inputs prior to a classification decision. The IGN demonstrated increased classification accuracy relative to more basic network designs and its further development was prompted.

Roitblat et al. (1993) augmented the biomimetic features of the IGN by developing a computational model of the dolphin ear that was used as a pre-processor of echo spectrum inputs. The purpose of the model was to weight the spectral inputs according to the observed auditory sensitivity of the bottlenose dolphin. The model consisted of 30 overlapping bandpass filters scaled in sensitivity according to the spacing and density of hair and ganglion cells within the inner ear of the dolphin (Roitblat et al., 1993). Ear model sensitivity matched dolphin sensitivity to frequencies > 50 kHz, but the output did not match the dolphin sensitivity below 50 kHz (figure 1).

Inferring design from anatomical features is a logical step in the development of a computational ear model. However, inadequate understanding of the physiological processes associated with dolphin auditory system anatomy, and the translation of those processes within the central auditory pathways, limits the computational implementation of these processes. Evolutionary programming (EP) offers an alternative approach to improving model design that does not rely upon expert information of the system being modeled. Computationally analogous to natural evolutionary processes, EP algorithms optimize model structure through an iterative process of parameter variation and model evaluation (Bäck, 1996). EP has been applied to all manner of engineering control and design problems (Rao and Chellapilla, 1996), optimization theory (Choi, 1999), and biological system modeling (Just et al., 2000), and is becoming increasingly popular as a design and optimization tool across a broad range of scientific disciplines. As such, EP has demonstrated itself as an appropriate technique for improving the biomimetic nature of the dolphin ear model.

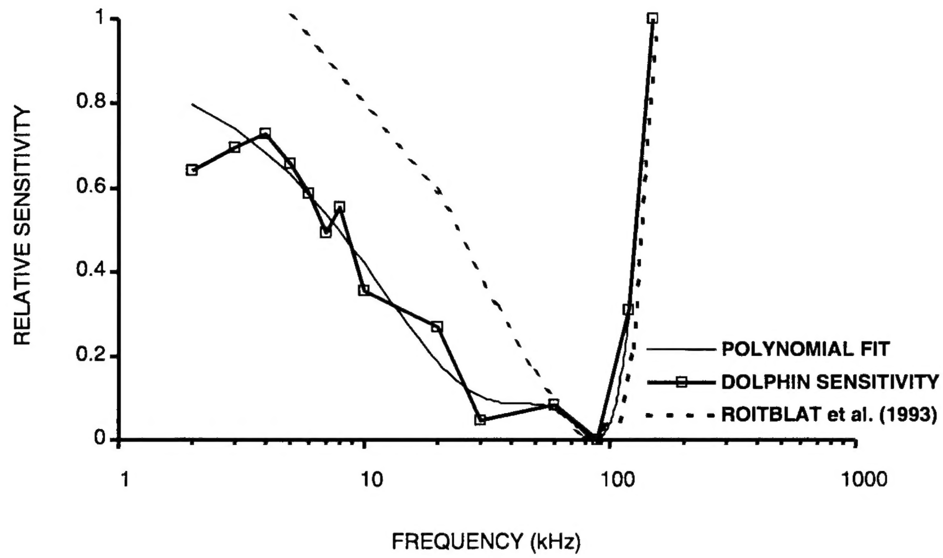

Figure 1. Comparison of the auditory sensitivity of the dolphin, the sensitivity of the dolphin ear model created by Roitblat et al. (1993), and the polynomial function to which the dolphin ear models were optimized.

The ear model, described hereafter, is constructed of a series of overlapping filters with each filter bandpass region described by an array of real valued numbers. The product of a filter array and the frequency spectrum of any signal produces a weighted output of the signal's spectrum. The combined weighting of all filters produces an output analogous to the signal scaling expected from the frequency-dependent sensitivity of the dolphin ear. This report details the optimization of a bandpass ear model to the auditory sensitivity of the dolphin through the implementation of EP.

SCALED AMPLITUDE MODELS

Methods

The design of several ear model architectures was attempted. Ear models were produced with either 1) scaled amplitude responses and a fixed range of center frequency distributions, or 2) with biomimetic dynamic range simulation and a variable range of center frequency distributions. Frequency resolution of the former model type was limited to ~0.98 kHz, and that of the latter to ~0.49 kHz. Within each category models were built in which filters were defined either by a pseudo-Gaussian (PG) function or a rounded exponential (ROEX) function.

Pseudo-Gaussian Design (PG)

In order to test the ability of the EP to optimize a model loosely based upon filter structures defined in the original bandpass ear model (Roitblat et al., 1993), bandpass filters were constructed from a modified Gaussian distribution. Center frequency (μ) of the filter (the frequency of maximum sensitivity) was defined as the mean of the Gaussian distribution. Filter shapes were modified to control for amplitude modulation as a function of standard deviation (σ) by removing σ from the denominator of the Gaussian distribution equation, thus producing the PG distribution. The resulting equation describing filter shape then became

$$\frac{1}{\sqrt{2\pi}}\exp(-\frac{1}{2}(\frac{x_i-\mu}{\sigma})^2)$$

where x_i is the i^{th} point on the distribution curve. Each filter was described by a 256 bin vector with each bin corresponding to a ~ 0.98 kHz width such that $i \in \{1, 2, 3, \ldots, 256\}$ and the frequency range covered by the filter shape was ~ 1 to 250 kHz.

Center frequencies (μ) were distributed from 1 to 120 kHz and filter μ was determined as a fractional power of the frequency range. This spacing was implemented to approximate the non-uniform clumping of characteristic frequencies observed on the mammalian basilar membrane (Geisler and Cai, 1996; Greenwood, 1990). The equation was

$$\mu_j = 120^{\frac{f_j}{F_n}}$$

where F_n is an integer defining the number of filters in the model, f_j is the j^{th} filter, and μ_j is the center frequency of the j^{th} filter, where $j \in \{1, 2, 3, \ldots, F_n\}$.

Shape and sensitivity of the bandpass region was determined by implementing a frequency-dependent amplitude-scaling factor (S) and a variable controlling the 3-dB frequency bandwidth (Q_3) in the spectral power domain. The scaling factor was determined as a base variable taken to a negative fractional power of the frequency range such that

$$S = y^{(\frac{f_j}{F_n}-1)}$$

where y is the base variable. This factor is analogous to the scaling used by Roitblat et al. (1993), which was based upon hair cell densities along the basilar membrane.

The variable Q_3 was defined as the ratio of μ to the –3 dB bandwidth of the filter in the spectral domain. This value was determined as an exponential function of filter center frequency and subsequently substituted into the base PG equation for σ. The relationship between σ and Q_3 was

$$\sigma = \frac{\mu_j}{\alpha Q_3}$$

where $\alpha = 2.351$ (α was empirically derived for the PG distribution in the power domain). Substitution for σ and μ and incorporation of the S into the PG distribution formed the equation describing filter shape and placement.

$$\frac{S}{\sqrt{2\pi}}\exp^{-\frac{1}{2}((x_i-(120)^{\frac{f_j}{F_n}})/(\frac{120^{\frac{f_j}{F_n}}}{2.351\,Q_3}))^2}$$

Rounded Exponential (ROEX) Design

A second series of models was created with filter shapes determined using a rounded exponential (ROEX) function (Patterson et al., 1982), a function commonly used to describe filter shapes in auditory models. This type of filter design was implemented to determine whether the interaction of ROEX filters produced an ear model with better sensitivity matching across the range of dolphin hearing than that developed with the more generic PG design. The ROEX function used was

$$(1+pg)\exp(-pg)$$

where g is the absolute relative frequency deviation from peak sensitivity (μ), and p defines filter quality (i.e., a variable similar to Q_3). The value of g was determined as

$$g = |(x_i - \mu_j)/\mu_j|$$

where μ_j is the peak frequency of the j^{th} filter and $j \in \{1, 2, 3, \ldots, F_n\}$. Filter quality parameter (p) was determined as a logarithmic function of μ such that

$$p = m * \log(\mu_j) + b$$

where m and b are constants. Each filter was described by a 256 bin array with each bin corresponding to ~ 0.98 kHz.

Factors dictating roll-off of the filter below center frequency and a weighting factor determining the skew of the low frequency tail were incorporated into the ROEX equation producing

$$A[(1 + pg)\exp(-pg)] + B[(1 + rg)\exp(-rg)]$$

where r is the parameter determining roll-off of the filter in the tail portion, and A and B serve to adjust the slopes of the passband and tail regions of the filter (Patterson et al., 1982; Rosen et al., 1998). The value of r was set as an arbitrary proportion of filter quality such that

$$r = zp$$

The value B was set as a linear function of filter peak frequency (μ_j) (estimates by A. Supin, pers. comm.) such that

$$B = 1/(\beta\mu_j)$$

Since A and B adjust the magnitude of the filter components, the sums of the separate effects must equal unity. Thus

$$A = 1 - B$$

A scaling factor identical to that applied in the PG model was applied to each generated filter shape. Filters were spaced according to the same center frequency distribution equation given for the PG model. (Note: in the ROEX model, μ designated filter peak frequency as opposed to filter center frequency in the PG model.)

The Evolutionary Program (EP)

Variables determining filter shape and distribution were submitted to an EP scheme with self-adaptive mutation (Fogel, 1995). Mutation was controlled via a Cauchy mutation operator (Chellapilla and Fogel, 1997). Table 1 lists the parameters submitted to the evolutionary process, i.e., the variables used to create the filter shapes. A collection of these variables constituted an "individual," designated Λ. The collection of all Λ determined the "population."

Initialization: The "parents" of a starting population, Λ_i (where $i = 1, 2, 3, \ldots, \tau$ and τ is an integer determining the size of the "parent population"), were initialized with the same filter number (F_n), either 40, 80, or 160. Other parameter values were randomly initialized within a user-defined range. For the PG model, initial bounds for y and the slope (m), intercept (b), and coefficient of the exponent (x) were set at {0, 10}, {0, 10}, {0, 2}, and {0, 0.025}, respectively. Standard deviation (σ_{EvPg}) for each parameter was initially set at 0.5, 0.5, 0.15, and 0.001, respectively. For the ROEX model, initial bounds for m, b, z, β, and y were {0,5}, {0,10}, {0,1}, {0, 20}, and {0,10}, respectively. Initial σ_{EvPg} applied to each parameter was 1, 1.5, 0.15, 3, and 1.5, respectively.

Table 1. Parameter values with initialization limits, initial standard deviations, and description of parameter function for the Scaled Amplitude Models. Parameters are grouped according to the function describing the filter shape.

Parameter	Minimum Initialization Limit	Maximum Initialization Limit	Initial Standard Deviation	Definition
PG Model				
y	0	10	0.5	base value for filter amplitude scaling
m	0	10	0.5	slope of the equation determing Q
b	0	2	0.15	intercept of the equation determing Q
x	0	0.025	0.001	coefficient of the exponent in the equation determing Q
F_n	(a)	(a)	(b)	filter number
ROEX Model				
y	0	10	1.5	base value for filter amplitude scaling
m	0	5	1	slope of the equation determing filter quality (p)
b	0	10	1.5	intercept of the equation determing p
z	0	1	0.15	slope of equation determing filter tail length (r)
F_n	(a)	(a)	(b)	filter number
β	0	20	3	coefficient of filter peak amplitude (μ) used in determining filter magnitude adjustment

(a) Filter number explicitly set to 40, 80, or 160

(b) Probabilistic mutation limited to integer step sizes of $\pm$ 2

Mutation: After initialization, each Λ_i was cloned and mutated to form the "offspring," $\Lambda_{\tau+i}$. Values of F_n were mutated in a probabilistic manner such that there was an equal probability that F_n would increase by 1 or 2, decrease by 1 or 2, or stay the same, if $20 \leq F_n \leq 200$. If F_n reached boundary values, there was an equal probability that F_n would increment by 1 or 2, if at the lower bound, decrement by 1 or 2, if at the upper bound, or remain unchanged. Real valued parameters were mutated via a Cauchy random variable (Chellapilla and Fogel, 1997). (For the PG model these parameters were: the amplitude scaling value (*y*) and the slope (*m*), intercept (*b*), and coefficient (*x*) of the exponent for the equation determining Q_3. For the ROEX model these parameters were: the amplitude scaling value (*y*), coefficient of center frequency (β) used to determine filter skirt magnitude adjustment, coefficient of filter quality (*z*) used to determine low frequency tail length, and the slope (*m*) and intercept (*b*) of the equation used to determine filter quality.)

Model Evaluation: Following mutation, parameter values from each individual ("parents" (Λ_i) and "offspring" ($\Lambda_{\tau+i}$)) were inserted into a filter function (PG or ROEX) to create a bank of filters. Each filter bank was evaluated for its sensitivity through a simulated audiometric assessment. A library of noise (N) and signal + noise (S+N) trials was created to test the sensitivity of the filters. Each library consisted of a 256x5000 matrix with each element of each row corresponding to a binwidth of ~ 0.98 kHz, i.e., equivalent to the frequency distribution described for the filter arrays. Each bin was initialized with randomly generated "noise" values ranging from 0.00 to 0.25. In the S+N library a real

valued "signal" of 0.55 was added to the bin corresponding to a given frequency. For instance, to add a signal to the 5 kHz frequency of the S+N library, 0.55 was added to the value of the 5th bin of each row of the library. This matrix thus became the 5 kHz S+N library, or (S_5+N). This procedure was conducted for frequencies of 1 kHz and from 5 to 150 kHz in 5 kHz increments, resulting in 31 libraries. Libraries were created to standardize the stimuli with which the filter banks were tested. This eliminated potential differences that could have been introduced by random noise and allowed comparison across repeated runs of the EP.

The response of the filters to N trials ($\mathbf{R}_\mathrm{N}$) and S_f + N trials ($\mathbf{R}_{\mathrm{SN}_f}$) was derived by multiplying the filter matrix (**F**) by the rows of the N library, and rows of the S_f + N library, respectively, for a given test frequency such that

$$\mathbf{R}_\mathrm{N}(i) = \mathbf{F} * \mathbf{N}(i), \quad i = 1, 2, 3, \ldots, 5000$$
$$\mathbf{R}_{\mathrm{SN}_f}(i) = \mathbf{F} * \mathbf{SN}_f(i), \qquad i = 1, 2, 3, \ldots, 5000$$

where **N** and $\mathbf{SN}_f$ represent the row vectors of the N library and the (S_f + N) library at frequency f. A squared-difference (**SD**) vector was then determined as

$$\mathbf{SD}(i) = [\mathbf{R}_{\mathrm{SN}_f}(i) - \mathbf{R}_\mathrm{N}(i)]^2, \qquad \mathrm{i} = 1, 2, 3, \ldots, 5000$$

and the sensitivity metric (ϕ_f) for the tested frequency determined as

$$\phi_f = 0.0002 \sum_{i}^{5000} \sqrt{\sum_{j}^{F_n} \mathrm{SD}(i,j)}$$

where F_n denotes the number of filters in the model. The process was repeated for all values of f, i.e., all 31 test frequencies.

The values of ϕ_f for all f were normalized from 0 to 1 to form the normalized response curve of the ear model (T_e). A normalized threshold curve of the bottlenose dolphin was generated as a compilation of experimentally determined thresholds for frequencies from 1 to 8 kHz (Johnson, 1968) and 10 to 150 kHz (Brill et al., 1997). A smoothed audiometric shape (T_d) was generated from the points with a 6th order polynomial function ($r^2 = 1.00$; figure 1). The normalized response curve of the ear model was compared to the normalized threshold curve of the bottlenose dolphin at 19 different frequencies (2, 3, 4, and 5 kHz, and 10 to 150 kHz at 10 kHz intervals). The absolute value of the maximum deviation between the two curves was used as the performance metric (P_m) for tournament selection, such that for

$$d(i) = \left|T_d(i) - T_e(i)\right|$$

where T_d is the function representing the dolphin sensitivity curve, T_e is the normalized output of the ear filter bank, $i \in \{2, 3, 4, 5, 10, 20, 30, \ldots, 150\}$ representing the comparison frequencies, and d is the difference between the functions at frequency i,

$$P_m = \mathrm{Max}\ (d(i))$$

The value of P_m thus gives a measure of the goodness of fit between the sensitivity of the ear filter model and the behaviorally determined audiogram of the bottlenose dolphin.

Selection: Following model evaluation, selection of parameter sets for inclusion in the next generation was determined via tournament selection with a tournament size of 10 (Goldberg and Deb, 1991). During tournament selection, the P_m value of each ear model was compared against the P_m

values of 10 other randomly selected models from within the population. The better performing of the two models from each comparison, i.e., the model with the lesser P_m value, received a "win." After all models were evaluated, the total number of "wins" for each individual was tabulated and the members of the population ranked according to the number of "wins." The half of the "population" with the greatest number of "wins" was selected as the "parent" group for the next generation. All other individuals were eliminated from the population.

The value of τ (parent population size) was set at 20 for all trials. Each generation each "parent" (Λ_i) produced one "offspring" ($\Lambda_{\tau+i}$), i.e., 20 "parent" parameter sets produced 20 "offspring" parameter sets, which is equivalent to a (20+20) evolutionary algorithm (Schwefel, 1981). Computer trials were terminated when no improvement in the P_m of the best individual of the population occurred over 50 to 100 generations. Three trials with F_n initialized at 40, 80, or 160 were performed for a total of nine trials per model type (PG or ROEX).

Computing Facilities

All optimization trials were run at the Navy High Performance Computing Center at Space and Naval Warfare Systems Center, San Diego (SSC San Diego) on a Hewlett-Packard V2500 multi-processor system. The V2500 utilized 16 440-MHz 4-way superscalar PA-8500 processors and 16 GB of RAM. All code was written in aC++, the HP version of C++ designed for use on HP Unix systems (see appendix 1). Evolutionary programming code was multithreaded in order to utilize the parallel-distributed processing capabilities of the V2500 system. Multithreading was performed according to current POSIX standards and through inclusion of pthread.C source libraries specifically supplied for the HP V2500.

Results

Pseudo-Gaussian Design

Final models from all trials used between 27 and 45 filters (table 2). Values of Q_3 ranged from 1.4 to 2.8. Differences in maximum and minimum values of Q_3 for all other models were no greater than 0.6 and several models approached a constant-Q_3 configuration.

Figure 2 compares the sensitivity of the best performing model to the smoothed dolphin audiogram and the sensitivity of the original dolphin ear model (Roitblat et al., 1993). This model consisted of 27 filters with values of Q_3 ranging from ~ 1.4 to 2.8 across the measured frequency range. The optimal amplitude scaling value (y) was 3.91. The maximum deviation between the observed dolphin hearing sensitivity and the best performing ear model with PG designed filters was 0.08.

All computational PG models demonstrated maximum deviations less than 0.12 from the behaviorally measured relative auditory sensitivity of the bottlenose dolphin. Greatest deviations in sensitivity matching occurred at 5 kHz, 30 kHz, and 130 kHz. Deviations at 130 kHz were less notable than deviations at lower frequencies due to the steep slope of the threshold curve above 100 kHz.

Table 2. Parameter values and maximum deviation from observed dolphin auditory sensitivity for the best performing pseudo-Gaussian models.

Trial Number	*m*	*x*	*b*	*y*	Filter Number	Maximum Deviation
40 initial filters						
1	0.03	1.27E-03	1.86E+00	2.42	40	0.11
2	1.36	5.63E-03	7.00E-02	3.91	27	0.08
3	1.56	2.50E-03	5.56E-05	2.98	33	0.1
80 initial filters						
1	0.2	7.34E-03	1.53E+00	2.67	35	0.1
2	0.05	2.00E-02	1.74E+00	3.13	28	0.09
3	0.06	2.00E-02	2.00E+00	2.79	34	0.1
160 initial filters						
1	1.91	1.40E-04	1.00E-10	2.46	41	0.11
2	0.24	1.36E-03	1.59E+00	2.45	38	0.11
3	0.36	7.06E-05	1.66E+00	2.43	45	0.11

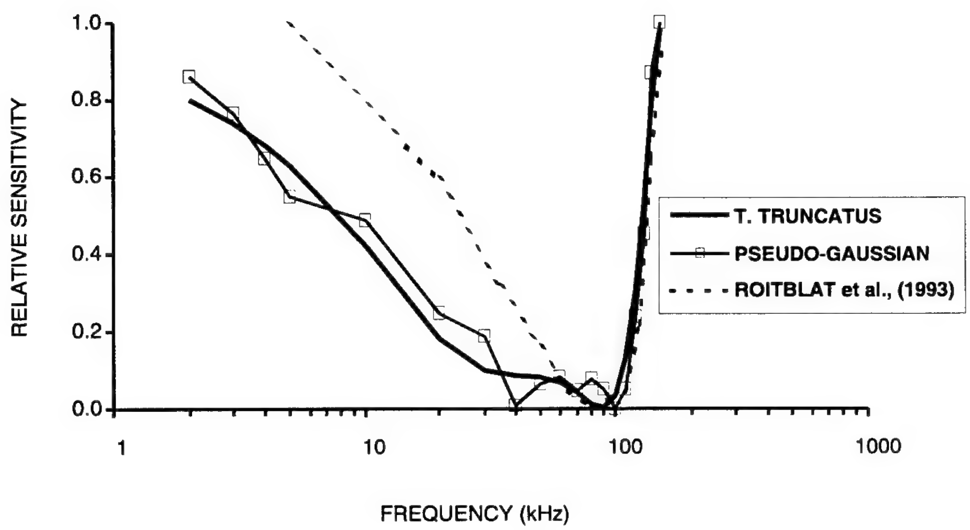

Figure 2. Comparison of the best performing scaled-amplitude model created with the PG filter design to both the observed dolphin sensitivity and the sensitivity of the Roitblat et al. (1993) model.

In order to determine the similarity in performance of the models, comparisons were made between the frequency-dependent sensitivities of the best performing model from each optimization trial. Deviations between the outputs of final models were greatest between 110 to 130 kHz and ranged from 0.10 to 0.17. Differences were less than 0.04 for all other frequencies tested.

Rounded Exponential Design

Optimal filter number for all models was 37 and amplitude scaling values (y) were stable, differing by no more than 0.55 (table 3). Filter quality (p) ranged from 7.3 to 11.3 across all model configurations, but differed by a maximum of 1.5 for all filters within a configuration. For three of the models, p approached a constant value. Greatest deviations in sensitivity matching typically occurred at 2 kHz, 5 kHz, and 140 kHz (figure 3).

Table 3. Parameter values and maximum deviation from observed dolphin auditory sensitivity for the best performing ROEX models.

Trial Number	m	b	z	y	β	Filter Number	Maximum Deviation
40 initial filters							
1	1.00E-10	11.30	61.85	2.13	24.30	37	0.13
2	0.09	10.88	0.76	2.22	16.19	37	0.13
3	0.07	10.92	14.53	2.19	249.47	37	0.13
80 initial filters							
1	0.74	7.31	0.01	2.68	8.58	37	0.13
2	0.42	9.19	2.30	2.38	58.38	37	0.13
3	0.71	7.78	7.51	2.57	27.08	37	0.13
160 initial filters							
1	0.65	8.10	2.04	2.55	687.71	37	0.13
2	0.45	9.08	360.19	2.40	5943.44	37	0.13
3	0.63	8.15	0.06	2.53	1087.13	37	0.13

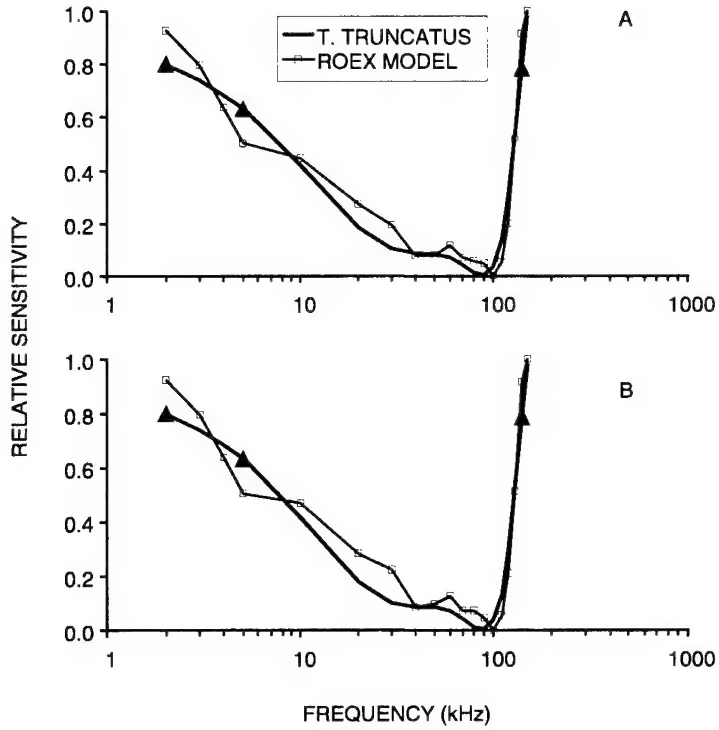

Figure 3. Comparison of the output of two ROEX designed scaled-amplitude models to the observed auditory sensitivity of the dolphin. Triangles indicate frequencies at which maximum deviations between the curves occur.

In order to determine the similarity in performance of the models, comparisons were made between the frequency-dependent sensitivities of the best performing model from each optimization trial. The maximum deviation between the output of all ROEX models was 0.03 and always occurred at 30 kHz.

The maximum deviation between observed dolphin hearing sensitivity and the sensitivity of all evolved ROEX-based models was 0.13, regardless of the number of filters at initialization (figure 3). When considering the range of hearing covered by PG and ROEX models (2 to 150 kHz), the PG model provided a better overall fit to the observed dolphin sensitivity. However, when considering the frequency range of 40 to 100 kHz, better sensitivity matching was achieved by the ROEX model (see figure 2 and figure 3).

GAIN SIMULATION MODELS

Methods

Pseudo-Gaussian (PG) and Rounded Exponential (ROEX) Designs:

Equations determining filter shape utilized in the "Gain Simulation Models" were identical to those used in the "Scaled Amplitude Models" with the following exceptions:

1. Each filter was described by a 512 bin vector with each bin corresponding to a ~ 0.49 kHz width. Frequency range covered by the filter shape remained ~ 1 to 250 kHz.

2. The first bin of each filter array was set to zero to accommodate a DC offset. Thus for all filters, x_i, as described in "Scaled Amplitude Models" was implemented as $(x_i - 1)$ where $i \in \{2, 3, 4, \ldots, 512\}$.

3. Instead of utilizing a static frequency range for distribution of filters, e.g., 120 kHz in the "Scaled Amplitude Model", a variable was incorporated determining the top center frequency allowable (μ_t). Thus, the frequency range across which filters were distributed was allowed to evolve within the EP such that

$$\mu_j = (\mu_t)^{\frac{f_j}{F_n}}$$

4. The scaling factor (S) applied to both the PG and ROEX models was changed to a 4th order polynomial of the form

$$S = a_1 * \mu_j + (a_2 * \mu_j^{\,2}) + (a_3 * \mu_j^{\,3}) + (a_4 * \mu_j^{\,4}) + C$$

where μ is the filter center frequency (PG) or frequency of peak sensitivity (ROEX) and a_i ($i = 1, 2, 3, 4$) and C are variables submitted to the EP.

The Evolutionary Program

Variables determining filter shape and distribution were submitted to an EP scheme with self-adaptive mutation (Fogel, 1995) and a Cauchy mutation operator (Chellapilla and Fogel, 1997). Table 4 lists the parameters submitted to the evolutionary process. Changes from the EP described for the optimization of the "Scaled Amplitude Models" follow:

Initialization: All Λ_i were initialized with $F_n = 40$ and a $\mu_t = 120$. Other parameter values were randomly initialized within a user-defined range. For the PG model, initial bounds for the slope (m), intercept (b), and coefficient of the exponent (x) of the equation determining Q_3 were set at {0, 10}, {0, 2}, and {0, 0.025}, respectively. Initial bounds for the 4 coefficients (a_i) and intercept (C) of the scaling equation were {0, 10}, {0, 2}, {0, 1}, {0, 1}, and {0, 100}. Standard deviation (σ_{EvPg}) for each parameter was initially set at 0.5, 0.15, 0.001, 0.5, 0.15, 0.05, 0.05, and 5, respectively. For the ROEX model, initial bounds for m, b, z, and β were {0,5}, {0,10}, {0,1}, and {0, 20} and the initial σ_{EvPg} applied to each parameter was 1, 1.5, 0.15, and 3, respectively. Initial bounds and σ_{EvPg} for the four coefficients and intercept of the scaling equation were identical to that used in the PG design.

Mutation: All coefficients (a_i) and the intercept (C) of the equations determining the scaling factor (S) were mutated via a Cauchy random variable. The variable μ_t was mutated in a probabilistic manner such that there was an equal chance that μ_t would increase by 1 or 2, decrease by 1 or 2, or remain the same. All other variable mutations followed the method described under "Scaled Amplitude Models."

Model Evaluation: Following mutation, parameter values from each individual in the population ("parents" (Λ_i) and "offspring" ($\Lambda_{\tau+i}$)) were inserted into a filter function (PG or ROEX) to create a bank of filters. Each filter bank was evaluated for its sensitivity through a simulated audiometric assessment. Instead of using a series of N and S+N trials (see "Scaled Amplitude Models"), a library of impulsive signals was generated to test the filters. The library consisted of a 512x512 matrix (**T**) with each element of each row corresponding to a binwidth of ~ 0.49 kHz, i.e., equivalent to the frequency distribution described for the filter arrays. All elements were initially set to zero. In order to create a computational analog of an impulsive test signal at successive frequencies for each spectral bin,

Table 4. Parameter values with initialization limits, initial standard deviations, and description of parameter function for the Gain Simulated Models. Parameters are grouped according to the function describing the filter shape.

Parameter	Minimum Initialization Limit	Maximum Initialization Limit	Initial Standard Deviation	Definition
PG Model				
m	0	10	0.5	slope of the equation determining Q
b	0	2	0.15	intercept of the equation determining Q
x	0	0.025	0.001	coefficient of the exponent in the equation determining Q
a_1	0	10	0.5	1st coefficient of the scaling equation
a_2	0	2	0.15	2nd coefficient of the scaling equation
a_3	0	1	0.05	3rd coefficient of the scaling equation
a_4	0	1	0.05	4th coefficient of the scaling equation
C	0	100	5	intercept of the scaling equation
μ_t	(a)	(a)	(b)	maximum characteristic frequency
F_n	(a)	(a)	(b)	filter number
ROEX Model				
m	0	5	1	slope of the equation determining filter quality (p)
b	0	10	1.5	intercept of the equation determining p
z	0	1	0.15	slope of equation determining filter tail length (r)
a_1	0	10	0.5	1st coefficient of the scaling equation
a_2	0	2	0.15	2nd coefficient of the scaling equation
a_3	0	1	0.05	3rd coefficient of the scaling equation
a_4	0	1	0.05	4th coefficient of the scaling equation
C	0	100	5	intercept of the scaling equation
μ_t	(a)	(a)	(b)	maximum characteristic frequency
F_n	(a)	(a)	(b)	filter number
β	0	20	3	coefficient of filter peak amplitude (μ) used in determining filter magnitude adjustment

(a) F_n = 40 and μ_f = 120 for all trials

(b) Probabilistic mutation limited to integer step sizes of $\pm$ 2

$$\mathbf{T}(i,i) = 1.0, \quad i = 1, 2, 3, \ldots, 512$$

for all i.

The response of the filters (**F**) to **T** trials ($\mathbf{R}_\mathbf{T}$) was derived by multiplying the filter matrix by the row of the impulse signal library for a given test frequency (f) such that

$$\mathbf{R}_\mathbf{T}(f) = \mathbf{F} * \mathbf{T}(f),$$

where **T** represent the row vector of the impulse signal library and

$$f = (i-1) * 0.49\,, \quad i = 1, 2, 3, \ldots, 512$$

where f is measured in kHz. The sensitivity metric (ϕ_f) for the tested frequency was then determined as

$$\phi_f = \sum_{j}^{F_n} \mathrm{R_T}(i,j)\,, \quad i = 2, 3, 4, \ldots, 512$$

where F_n denotes the number of filters in the model. The values of ϕ_f for all f were transformed to dB re: (maximum ϕ_f) to form the response curve of the ear model (T_e).

$$T_e(i) = 20 * \log_{10}\left({}^{\phi_f(i)} \Big/ {}_{\phi_{f\mathrm{MAX}}} \right)$$

A threshold curve of the bottlenose dolphin (T_d) was generated as a compilation of data points taken from Johnson (1 to 8 kHz; 1968) and Brill et al. (10 to 150 kHz; 1997) and converted to dB re: (maximum sensitivity). The response curve of the ear model was compared to the threshold curve of the bottlenose dolphin at incremental frequencies of 0.98 kHz. For frequencies on T_d for which experimentally obtained sensitivities have not been obtained, sensitivities were estimated via linear interpolation. The absolute value of the maximum deviation between the two curves was used as the performance metric (P_e) for tournament selection, such that for

$$d(i) = \left| T_d(i) - T_e(i) \right|$$

where T_d is the function representing the dolphin sensitivity curve, T_e is the output of the ear filter bank, $i \in \{1, 2, 3, \ldots, 255\}$ and d is the difference between the functions at frequency (i * 0.98 kHz),

$$P_m = \max\,(d(i))$$

Selection: Tournament selection was performed identically to the method described previously (see "Scaled Amplitude Models"). Computer trials were terminated after 1500 generations. Six trials were performed for each model type (PG or ROEX).

Computing Facilities

All optimization trials were run at the Navy High Performance Computing Center (SSC San Diego) on a Hewlett-Packard V2500 multi-processor system. The V2500 utilized 16 440-MHz 4-way superscalar PA-8500 processors and 16 GB of RAM. All code was written in aC++, the HP version of C++ designed for use on HP Unix systems (see appendix 2).

Results

Pseudo-Gaussian Design

The number of filters used in each model was highly variable, ranging from 19 to 214 (table 5). In contrast, μ_t was less variable ranging from 75 to 97. Values of Q_3 ranged from 1.2 to 3.7. Differences in maximum and minimum values of Q_3 for all other models were no greater than 2.1 and one model converged upon a constant-Q_3 configuration (optimization #3, see table 5).

Table 5. Parameter values and maximum deviation from observed dolphin auditory sensitivity for the best performing pseudo-Gaussian models. Maximum deviations are in dB re: maximum sensitivity of the dolphin.

Trial Number	*m*	*x*	*b*	μ_t	Filter Number	Maximum Deviation (dB)
1	0.46	1.12E-02	8.32E-01	75	74	11.4
2	3.23	1.31E-03	3.19E-02	97	32	13.2
3	2.95	1.11E-04	1.47E-04	89	19	15.1
4	1.19	4.37E-03	2.76E-01	81	61	8.9
5	1.09	1.14E-02	9.23E-02	94	214	11.3
6	1.23	4.55E-03	2.14E-01	82	121	9.0
	a_1	a_2	a_3	a_4	*C*	
1	9.73	1.49	1.24E+00	4.29E-06	1.80E+02	
2	56.33	2.58	5.04E-06	1.00E-10	1.00E-10	
3	2877.98	0.35	9.72E-01	4.03E-06	2.69E+02	
4	18.08	2097.56	9.83E-05	8.13E-04	5.67E+02	
5	0.20	93.03	9.08E-02	1.00E-10	1.00E-10	
6	1468.44	656351.00	2.53E+02	1.29E+00	7.71E+03	

Figure 4 demonstrates the maximum deviation between observed dolphin hearing sensitivity and the sensitivity of the best performing ear model with PG designed filters (P_m = 8.9 dB re: max sensitivity). Maximum deviations from dolphin sensitivity occurred at 3, 10, 30, and 145 kHz (figure 4). This model consisted of 61 filters with values of Q_3 ranging from ~ 1.5 to 2.0 across the measured frequency range.

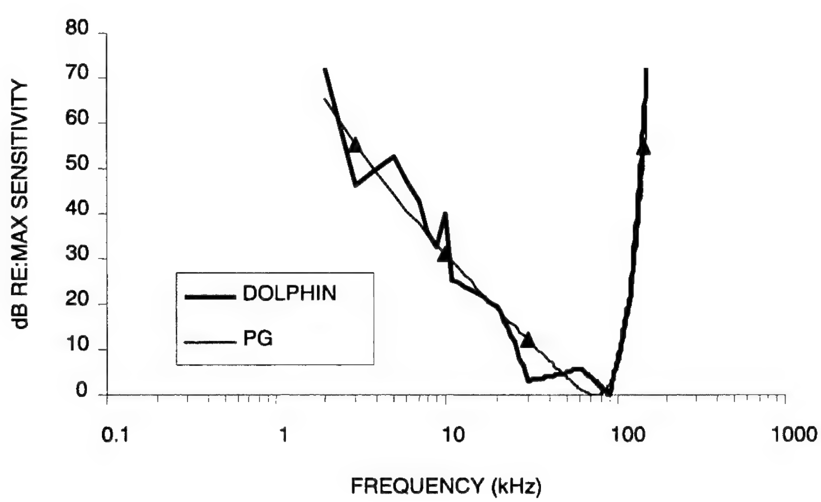

Figure 4. Comparison of the best performing gain simulation model using a PG filter design to the actual auditory sensitivity of the dolphin. Triangles signify frequencies at which maximum deviations between the two curves occur.

All models implementing PG designed filters demonstrated maximum deviations less than 15 dB from the behaviorally measured auditory sensitivity of the bottlenose dolphin. Mean maximum deviation was 11.5 dB. Greatest deviations in sensitivity matching typically occurred at 2 and 30 kHz. As in other models, deviations above 100 kHz were graphically less obvious than deviations at lower frequencies because of the steep slope of the threshold curve.

In order to determine the similarity in performance of the models, comparisons were made between the frequency-dependent sensitivities of the best performing model from each optimization trial. Deviations between the outputs of the different models were greatest between 111 to 150 kHz where they ranged from 17.0 to 22.5 dB.

Rounded Exponential Design

The optimal number of filters used in each model ranged from 35 to 92 (table 6). The range of filter quality (p) used in each model was variable with both constant p values and ranges from 1.1 to 5.7 being observed. Considering all models together, p ranged from 1.1 to 10.4. The two ear models that utilized constant-p ROEX filters (p of 10.2 and 10.4) had the closest fit to the dolphin sensitivity curve (P_m equal to 10.0 and 10.4, respectively). Greatest deviations in sensitivity matching occurred at 2 and 30 kHz for every ear model and at 120 kHz in three of the six models.

Table 6. Parameter values and maximum deviation from observed dolphin auditory sensitivity for the best performing ROEX models. Maximum deviations are in dB re: maximum sensitivity of the dolphin.

Trial Number	m	b	z	β	μ_t	Filter Number
1	1.90E+00	10.02	0.25	13.92	88	44
2	1.18E-03	10.13	1.69	0.50	77	92
3	9.35E-01	7.07	95.34	1162.17	77	35
4	2.49E+00	0.97	5.28	0.44	79	47
5	1.96E+00	3.19	1.10	29.52	80	89
6	1.18E-02	10.42	1.85	7392.32	77	60

	a_1	a_2	a_3	a_4	C	Maximum Deviation
1	5.03E+01	5.75E+00	1.00E-10	1.00E-10	8.91E-04	13.3
2	1.60E+01	4.18E+00	4.25E-09	8.52E-09	3.53E-02	10.0
3	1.00E-10	1.03E+00	6.17E-04	1.00E-10	4.22E+00	11.3
4	1.80E+00	6.05E+02	1.00E-10	1.00E-10	5.07E+01	11.0
5	1.68E+01	1.92E+05	3.74E-02	1.00E-10	2.40E+02	10.9
6	5.96E+02	1.97E+02	8.53E-03	1.00E-10	4.06E+00	10.4

In order to determine the similarity in performance of the models, comparisons were made between the frequency-dependent sensitivities of the best performing model from each optimization trial. The maximum deviation between the output of all ROEX models was 21.1 dB and occurred at 150 kHz. Deviations >10.0 to 21.1 dB occurred above 133 kHz and directly increased with frequency.

Figure 5 demonstrates the maximum deviation between observed dolphin hearing sensitivity and the sensitivity of the best performing ROEX-based model (P_m = 10.0 dB re: maximum sensitivity). Maximum deviations occurred at 2, 30, 120, and 150 kHz (figure 5). This model consisted of 92 filters, a maximum center frequency (μ_t) of 77 kHz, and constant p values of 10.1 across the measured frequency range.

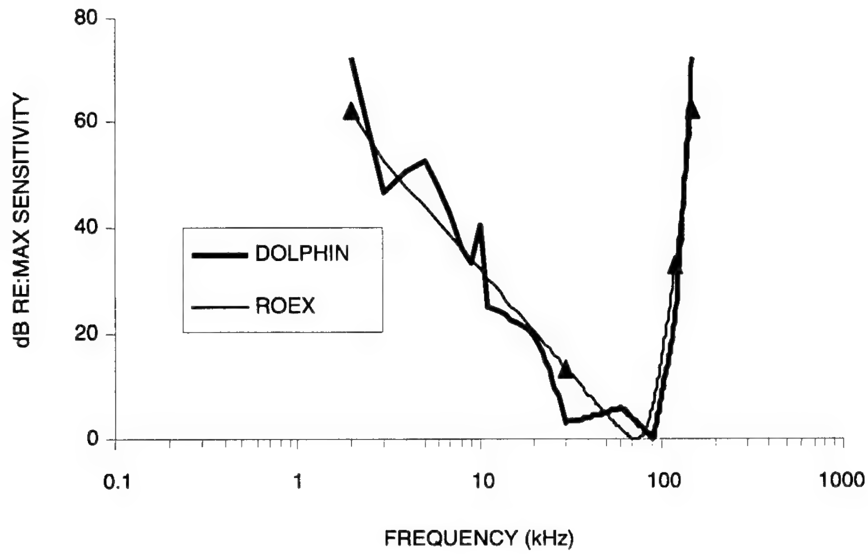

Figure 5. Comparison of the best performing gain simulation model using a ROEX filter design to the actual auditory sensitivity of the dolphin. Triangles signify frequencies at which maximum deviations between the two curves occur.

Discussion

Through the use of EP, a suite of dolphin ear models has been designed that can be used as frequency spectrum filters and implemented as preprocessors to target echo classifiers. Two groups of models were created consisting of either filter banks scaled for spectral inputs or filter banks that emulate the actual auditory range of the bottlenose dolphin. Within these model types, filters were created based upon either PG or ROEX distributions. All optimized models, scaled or otherwise, demonstrated a considerable improvement over the original bandpass filter model (Roitblat et al., 1993) by exhibiting sensitivity matching across the range of dolphin hearing.

Though targeted for incorporation into biomimetic mine countermeasure algorithms, these models can generally be used as auditory weighting functions. Depending upon whether amplitude-scaled or gain-simulated models are to be used, differences in the performance of the ROEX and PG filter designs should be considered prior to implementation. For instance, in the amplitude-scaled models, the smallest maximum deviations between model and dolphin sensitivity were observed when models were constructed with PG designed filters. However, frequencies at which the greatest deviations from dolphin sensitivity occurred were spread across the range of hearing. Models constructed from ROEX filters had sensitivities that deviated to a greater extent from the dolphin sensitivity, but maximum deviations were isolated to low ($\leq$ 5 kHz) and high ($\geq$ 140 kHz) frequency ends of the hearing range. The contribution of filtering effects at these frequencies should be reduced relative to the total output of the model because of the rapid decline in sensitivity above 100 kHz. Thus, if the

focus is on frequencies spanning the middle of the dolphin hearing range (e.g., 40 to 60 kHz), it would be more appropriate to use models based upon ROEX filters. In contrast, if the filtering effect across the entire range of hearing is desired, models based upon PG filters would be more appropriate.

Results of the scaled amplitude model optimizations utilizing PG filters suggest that near-optimal model construction was achieved when filter banks contained between 27 and 45 filters. Optimal design for ROEX-based models was likely achieved since all models evolved a design utilizing 37 filters and the greatest deviation between any two models was no greater than 0.03. In contrast, gain-simulated models were much more variable in their evolved structures, probably due to the additional degrees of freedom introduced by the addition of design variables (e.g., μ_t).

The filter numbers utilized by the models are similar to Johnson's (1968) estimated number of critical bands for the bottlenose dolphin. Values of Q_3 determined for the PG model ranged from 1.4 to 2.8 and are in close agreement with estimates derived from critical band measurements; Q estimates for 30, 60, and 120 kHz (measured at the critical band) are 1.8, 2.4, and 2.7, respectively (Au and Moore, 1990). Thus, even though the amount of expert information incorporated into model development was limited, the artificial systems demonstrate emergent properties analogous to the biological system.

The task of creating an artificial system capable of emulating the object detection and identification capabilities of the Navy's Marine Mammal Systems is daunting. Idealistically, this task can be approached by emulating the processes underlying echolocation (sound transmission, reception, and signal processing). The models described here attempt to model a component of the dolphin's receive system and thus contribute to the overall effort. Use of these models as preprocessors in biomimetic object classification systems increases the biomimetic nature of those systems by providing a better approximation of the peripheral auditory processing in the dolphin. Furthermore, such models can be used as auditory weighting functions (AWF). These AWF's can be applied to questions regarding the environmental impact of water-borne anthropogenic sound upon marine mammals such as the dolphin. Anthropogenic signals of concern can be filtered in order to predict how the peripheral auditory system of the dolphin attenuates frequency components of the signal. These models serve as a basis for the development of more advanced models and provide a framework upon which to build additional biomimetic components.

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APPENDIX 1A – SOURCE CODE
SCALED AMPLITUDE MODEL: PSEUDO-GAUSSIAN DESIGNED FILTERS

The source code for the evolutionary program created to optimize a series of pseudo-Gaussian designed bandpass filters to the relative auditory sensitivity of the bottlenose dolphin may be found at http://www.spawar.navy.mil/sti/publications/pubs/tr/1834/dolphinepcode.doc. The following source code and header files are present:

main.C	
app.C	app.h
member.C	member.h
eval.C	eval.h
nrutil.C	nrutil.h
interp.C	interp.h
random.C	random.h
objfns.C	objfns.h

The reader is referred to the text of the technical report for procedures on building the noise (N) and signal + noise (S+N) files used in testing the filters.

The code is written in aCC+ and aCC, the proprietary C++ and C language for HP UNIX systems. When porting to other UNIX systems, check the system-specific documentation to resolve cross-platform incompatibilities. Multithreading is achieved through implementation of the pthread libraries for the HP UNIX aCC programming language.

APPENDIX 1B – SOURCE CODE
SCALED AMPLITUDE MODEL: ROEX DESIGNED FILTERS

The source code and the header file for creating ROEX designed filters during scaled amplitude model creation and optimization can be found at http://www.spawar.navy.mil/sti/publications/pubs/tr/1834/dolphinepcode.doc. Most of the differences between this program and that described under appendix 1A are contained in the objfns.C source code. However, because the number of parameters necessary to create the ROEX filters differs from that of the pseudo-Gaussian filters, changes within app.C and member.C are necessary to ensure that the additional parameter values are reported in the log files.

Changes needed in app.C:

1. The function(s) AppGetAvg*() will need to be added to get the population average standard deviations for any additional parameter(s).
2. DisplayStats(), WriteInfoToFile(), WriteBestToFile(), and WriteDirect() need to be modified to write the value of additional parameters associated with the ROEX function to file.

Changes needed in member.C:

1. MemberGetAvgS*() needs to be added for each additional AppGetAvg*() function placed in app.C.

Code is written in aCC+ and aCC, the proprietary C++ and C language for HP UNIX systems. When porting to other UNIX systems, check the system-specific documentation to resolve cross-platform incompatibilities. Multithreading is achieved through implementation of the pthread libraries for the HP UNIX aCC programming language.

APPENDIX 2A – SOURCE CODE
GAIN-SIMULATION MODEL: PSEUDO-GAUSSIAN DESIGNED FILTERS

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main.C	
app.C	app.h
member.C	member.h
eval.C	eval.h
random.C	random.h
objfns.C	objfns.h

The reader is referred to the text of the technical report for procedures on building the impulse signal library used to test the ear filters.

Code is written in aCC+ and aCC, the proprietary C++ and C language for HP UNIX systems. When porting to other UNIX systems, check the system-specific documentation to resolve cross-platform incompatibilities.

APPENDIX 2B – SOURCE CODE
GAIN-SIMULATION MODEL: ROEX DESIGNED FILTERS

The source code and the header file for creating ROEX designed filters during gain simulation model creation and optimization can be found at http://www.spawar.navy.mil/sti/publications/pubs/tr/1834/dolphinepcode.doc. Most of the differences between this program and that described under appendix 2A are contained in the objfns.C source code. However, because the number of parameters necessary to create the ROEX filters differs from that of the pseudo-Gaussian filters, changes within app.C and member.C are necessary to ensure that the additional parameter values are reported in the log files.

Changes needed in app.C:

1. The function(s) AppGetAvg*() will need to be added to get the population average standard deviations for any additional parameter(s).
2. DisplayStats(), WriteInfoToFile(), WriteBestToFile(), and WriteDirect() need to be modified to write the value of additional parameters associated with the ROEX function to file.

Changes needed in member.C:

1. MemberGetAvgS*() needs to be added for each additional AppGetAvg*() function placed in app.C.

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14. ABSTRACT
A type of self-optimizing computer algorithm, called evolutionary programming, was used to create a number of models of the dolphin ear. The models consisted of a series of overlapping bandpass filters that varied in sensitivity and bandpass region and were distributed across the range of dolphin hearing. The evolutionary program iteratively varied the shape, number, and distribution of filters in each model and optimized the acoustic sensitivity of the model to the hearing sensitivity of the dolphin. Final models displayed acoustic sensitivities similar to the dolphin across the range of dolphin hearing. These bandpass models are frequency domain filters usable as preprocessors to biomimetic mine countermeasure classification/detection algorithms and auditory weighting functions in environmental compliance issues related to the interaction between marine mammal populations and anthropogenic sound.

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